Published in final edited form as:

Proc SPIE. 2013 March 13; 8669: . doi:10.1117/12.2007060.

Automatic Segmentation of Abdominal Wall in Ventral Hernia CT: A Pilot Study

Zhoubing Xu^{a,*}, Wade M. Allen^b, Benjamin K. Poulouse^c, and Bennett A. Landman^{a,b}

^aElectrical Engineering, Vanderbilt University, Nashville, TN, USA 37235

^bInstitute of Imaging Science, Vanderbilt University, Nashville, TN 37235

^cGeneral Surgery, Vanderbilt University Medical Center, Nashville, TN 37235

Abstract

The treatment of ventral hernias (VH) has been a challenging problem for medical care. Repair of these hernias is fraught with failure; recurrence rates ranging from 24–43% have been reported, even with the use of biocompatible mesh. Currently, computed tomography (CT) is used to guide intervention through expert, but qualitative, clinical judgments; notably, quantitative metrics based on image-processing are not used. We propose that image segmentation methods to capture the three-dimensional structure of the abdominal wall *and its abnormalities* will provide a foundation on which to measure geometric properties of hernias and surrounding tissues and, therefore, to optimize intervention. To date, automated segmentation algorithms have not been presented to quantify the abdominal wall and potential hernias. In this pilot study with four clinically acquired CT scans on post-operative patients, we demonstrate a novel approach to geometric classification of the abdominal wall and essential abdominal features (including bony landmarks and skin surfaces). Our approach uses a hierarchical design in which the abdominal wall is isolated in the context of the skin and bony structures using level set methods. All segmentation results were quantitatively validated with surface errors based on manually labeled ground truth. Mean surface errors for the outer surface of the abdominal wall was less than 2mm. This approach establishes a baseline for characterizing the abdominal wall for improving VH care.

Keywords

Segmentation; Level Set; Ventral Hernia; Abdominal Wall

1. INTRODUCTION

The management of ventral hernias (VH) remains a challenging problem for primary care physicians, surgeons, and patients. VHs include primary abdominal wall defects (e.g., umbilical hernias) and acquired incisional defects resulting from previous abdominal operations. Repair of these hernias is fraught with failure; recurrence rates ranging from 24–43% are reported, even with the use of biocompatible mesh [1]. Even in optimal conditions, VHs occur in up to 28% of patients undergoing abdominal operations [2, 3]. Recurrence of previously repaired VHs increases costs and morbidity to patients and can require multiple repairs. The common clinical problem of VH and wide variation in care present a unique opportunity for improvement in classification and outcomes. For each 1% reduction in

*zhoubing.xu@vanderbilt.edu; <http://masi.vuse.vanderbilt.edu>; Medical-image Analysis and Statistical Interpretation Laboratory, Department of Electrical Engineering, Vanderbilt University, Nashville, TN, USA 37235.

recurrence of VH after repair, an estimated annual cost savings of \$32 million could be realized [4].

Computed tomography (CT) is used to make qualitative clinical judgments about a particular patient's hernia for treatment and prognosis. However, the only quantitative metric currently in use is the transverse dimension of the hernia defect. We posit that the CT image obtained from these studies is underutilized and provides a potentially rich — and automated — means of better characterizing VH. Three-dimensional structural measurements based on computational tools have been the subject of extensive study in the brain in the search for biomarkers for clinical development of therapeutics [5], and have been targeted for therapeutic modifications and as surrogate endpoints in clinical trials (e.g., [6, 7]). These methods have yet to be applied to the abdominal wall.

We propose that image segmentation methods to capture the three-dimensional structure of the abdominal wall will provide a foundation on which to measure geometric properties of hernias and surrounding tissues. For example, given the segmentation, we will be able to numerically compute the area of disruption, volume of herniated tissue, degree of impact to muscles (ruptured versus displaced), and displacement/volumetric changes in abutting wall structures versus change at distant relatively normal tissues (Figure 1). Level set image processing methods can be ideally adapted to finding contours between objects of different intensity in the presence of noise, artifacts, and disruption through the use of tuned regularization criteria. In this pilot study, we establish the first step in a quantitative image analysis pipeline for VH, specifically: reproducible automated segmentation of the bony skeleton, skin, and outer abdominal wall in clinically acquired CT.

2. METHODS AND RESULTS

An inter-patient consistent coordinate system with reproducible biomarkers is needed for localization of VHs. To this end, we pursue robust, automated segmentation of bone skeleton, skin, and outer abdominal wall (Figure 2). First, we use approximate threshold methods to extract the intensity-significant bony structure, and use basic level set numerical methods with mathematical morphological operators to find the continuous surfaces of skin and outer abdominal wall.

2.1 Level Set

In the level set approach [8], an evolving surface is embedded as the zero level set of a higher dimensional level set function $\Phi(x, t)$, and propagates implicitly through the temporal evolution of Φ in terms of a given speed function F . $\Phi(x, t)$ is defined as signed distance function to the evolving surface with negative value inside the surface and positive outside. The speed function, which can be spatially varying, is usually determined by advection forces (e.g., constant inward or outward motion) and intrinsic geometry (e.g., mean curvature). The temporal evolution of the level set function can be prescribed in the following form,

$$\Phi_t + F|\nabla\Phi| = 0 \quad (1)$$

where $|\nabla\Phi|$ represents the normalized gradient of the level set function.

Image segmentation problems solved with level set methods usually integrate intensity and gradient information to construct the speed function.

$$F = F_{\nabla I} (w_{int} F_{int} + w_{curv} F_{curv}) \quad (2)$$

where F_{int} is defined to be positive within a given intensity range ($I_0 - d, I_0 + d$), and negative out of the range,

$$F_{int} = |I - I_0| - d \quad (3)$$

F_{curve} denotes the curvature force which smooths the level set function,

$$F_{curv} = \nabla \frac{\nabla \Phi}{|\nabla \Phi|} \quad (4)$$

$F_{\nabla I}$ is a speed term proposed by Malladi et al [9]. to stop the evolution at image edges. A typical form of this edge stopping term can be represented as follows,

$$F_{\nabla I} = \frac{1}{1 + |\nabla G_{\sigma} * I|^2} \quad (5)$$

where $|\nabla G_{\sigma} * I|$ denotes an image convolved with a Gaussian kernel with a standard deviation of σ . The appending of the edge stopping term translates the original region-based level set method into an edge-based approach. Effect of intensity force and curvature force can be weighted by W_{int} and W_{curv} .

2.2 Segmentation

2.2.1 Bone Skeleton—Bones can be identified as high intensity regions in CT images. We used threshold methods to efficiently segment the skeleton (not including cartilages). For the purpose of locating biomarkers, the limited field-of-view skeleton over the ventral CT scan was separated into four categories: (1) femur; (2) pelvis; (3) spinal vertebrae; (4) ribs, and any other bones surrounding the spine (e.g., sternum, scapula, etc.). We identify the structures based on the sizes and locations of the connected components after setting a threshold. In particular, we extracted the whole bone skeleton with a lower threshold (200 HUs), then with a higher threshold (800 HUs), determined the specific categories of the more detached components within that skeleton, and assign the categories to the undetermined regions in the skeleton, to the nearest category.

2.2.2 Skin—We constructed a region-based level set function with an intensity force centered at the intensity of fat (−100 HUs) and a substantial curvature force to help the evolving surface exclude the table and regularize the surface's shape (Figure 3). The skin has variable thickness around human body. This approach identifies the outer edge of the skin. Releasing the curvature constraints can lead the evolving surface to the inner edge, but in such cases, the evolving front level may enter the body.

Based on the two iliac crests and the ribs (three landmarks), we used the shortest spatial distances to these references to construct three coordinates. Normalized values under these coordinates were converted into RGB system to color the skin surface (Figure 4). This system is a putative trial for constructing inter-subject coordinates for VH metrics. Selection of biomarkers and regularization of the coordinates is an area of continuing investigation.

2.2.3 Outer Abdominal Wall—Outer abdominal wall is defined as the surface formed by muscles (e.g., rectus, oblique) and fascial connections (e.g., linea alba, linea semilunaris) encompassing the abdominal cavity. When a VH occurs, the segmentation of outer abdominal wall becomes challenging given varied appearances (Figure 4). The skin, with similar intensity (40 HUs) of the muscle, as well as the inflamed tissues greatly affects the performances of edge-based level set. In addition, the existence of intensity inhomogeneity usually makes the edge stopping function hard to discriminate the herniated regions from the noise tissues.

These problems were resolved by mathematical morphological operators. Morphological open and close operators are known as effective tools on binary images for filtering noise and filling holes respectively. In our experiments on all the four subjects, to clean the noise from the skin and fat tissues, we set a threshold (-60 HUs) to include all possible intensities of herniated regions, applied series open and close operators with 2-voxel wide disk structuring element, and selected the largest remaining connected components. This procedure may also lose some part of thin herniated walls. We continued with close operators with 20-voxel length line structuring elements at 0° , 45° , 90° , and 135° directions under axial view as well as another close operator with 10-voxel wide disk structuring element under axial, coronal, and sagittal views. Level set functions were designed to extract a smooth surface of the resulting regions after multiple morphological modifications were enhanced (Figure 3).

2.3 Quantitative Validation

Ground truth for all segmented structures (bones, skin, and outer abdominal wall) was manually labeled at sampled points for all subjects using the Medical Image Processing And Visualization (MIPAV) software. We created a grid of outer abdominal wall by labeling axial and sagittal wall contours approximately every 5cm (Figure 4). Bones and skin were labeled for axial contours every 15mm and 5 cm respectively.

Surface distances were calculated from every labeled truth points to automatically segmented structures. Mean surface errors for bones, skin, and outer abdominal wall were $2.24mm \pm 3.28mm$, $1.17mm \pm 0.88mm$, $1.58mm \pm 1.56mm$ respectively. The errors for two iliac crests varied from 1mm to 9mm.

3. DISCUSSION

In summary, we have presented a first approach to segmentation of the abdominal wall on CT data. Initial results on this small sample are highly promising as mean surface distances were less than 2 mm (less than 1 slice thickness). The presented dataset includes three patients with hernias and post-operative patient with inflammation, but no hernia (#2). Efforts to improve the overall accuracy and validate this approach on larger clinical dataset are ongoing.

The primary contribution of this work is that we have demonstrated a quantitative framework with which to classify abdominal anatomies relevant to abdominal wall disease. Perhaps surprisingly, this important structure has been largely neglected in the image processing literature. The proposed framework provides a quantitative basis for capturing abdominal wall structure and applying computer aided algorithms to evaluate and optimize VH repair.

In continuing efforts, we are interested in characterizing the abdominal wall composition, including the tissues in the narrowband (small area) around the outer fascia surface (including muscle, bone, fascia, organ, air, etc.). Using surface curvature models and tissue

classifications, we will seek to identify abnormalities and disruptions (hernias) in the abdominal wall. Ultimately, improved quantification of hernia and abdominal wall structure will lead us to have a better idea of whom to treat (or not treat) and with what type of repair. This would lead to standardization of care and ultimately, less waste in this commonly performed procedure that is currently rife with unnecessary variation in care.

Acknowledgments

This project was supported by ViSE/VICTR VR3029 and NIH 1R03EB012461.

References

1. Luijendijk RW, Hop WCJ, van den Tol MP, de Lange DCD, Braaksma MMJ, IJzermans JNM, Boelhouwer RU, de Vries BC, Salu MKM, Wereldsma JCJ. A comparison of suture repair with mesh repair for incisional hernia. *New England Journal of Medicine*. 2000; 343(6):392–398. [PubMed: 10933738]
2. Trimbos J, Smit IB, Holm JP, Hermans J. A randomized clinical trial comparing two methods of fascia closure following midline laparotomy. *Archives of Surgery*. 1992; 127(10):1232. [PubMed: 1417492]
3. Pans A, Elen P, Dewe W, Desai C. Long-term results of polyglactin mesh for the prevention of incisional hernias in obese patients. *World journal of surgery*. 1998; 22(5):479–483. [PubMed: 9564292]
4. Poulou B, Shelton J, Phillips S, Moore D, Nealon W, Penson D, Beck W, Holzman M. Epidemiology and cost of ventral hernia repair: making the case for hernia research. *Hernia*. 2011:1–5.
5. O'Connor JPB, Jackson A, Asselin MC, Buckley DL, Parker GJM, Jayson GC. Quantitative imaging biomarkers in the clinical development of targeted therapeutics: current and future perspectives. *The lancet oncology*. 2008; 9(8):766–776. [PubMed: 18672212]
6. Dickerson BC, Sperling RA. Neuroimaging biomarkers for clinical trials of disease-modifying therapies in Alzheimer's disease. *NeuroRx*. 2005; 2(2):348–360. [PubMed: 15897955]
7. Bielekova B, Martin R. Development of biomarkers in multiple sclerosis. *Brain*. 2004; 127(7):1463–1478. [PubMed: 15180926]
8. Osher S, Sethian JA. Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. *Journal of computational physics*. 1988; 79(1):12–49.
9. Malladi R, Sethian JA, Vemuri BC. Shape modeling with front propagation: A level set approach. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*. 1995; 17(2):158–175.

Figure 1.

Appearance of VH on CT. VH appear as disruptions to the abdominal wall on CT (A). Abdominal organs may herniate through the wall (as in B) or the wall may be inflamed but not herniated (as in C). Although the outer wall typically maintains an intact fascia sheath, it may be disrupted (as in D). Note the variety of body sizes, noise levels and texture/ inflammation in the abdominal fat in the four subjects.

Figure 2.

Flowchart of the proposed method. A high threshold is assigned to extract the whole bone skeleton, while a low threshold is used to divide the skeleton into different components. Relative position information is used to identify the specific type of bones. After skin is segmented by region-based level set method, two anterior iliac crests and all visible ribs are selected as biomarkers, based on which three coordinates were created. The skin is then colored with RGB values converted by the normalized shortest distances to the biomarkers. The segmented skin is also used as an initial start for the level set segmentation of outer abdominal wall. Morphological operators are used to release segmentation difficulties. Ground truth was manually labeled for all subjects (bones, skin, and abdominal wall) to calculate the surface errors of automatic segmentation.

Figure 3. Intermediate results of level set method of a single slice. (A) Skin segmentation initialized with a cube surface. (B) Outer abdominal wall segmentation initialized with the result of skin.

Figure 4.

Segmentation results for four subjects. The first column represents the results of bone skeleton and skin. The second column demonstrates the segmentation of outer abdominal wall (green) overlaid with grids of labeled ground truth (red). The third to the sixth columns show the intra- and inter- variability of abdominal wall over slices and the segmentation results of our approach (red).

Table 1

Empirical Errors for All Segmented Objects (all metrics in mm)

Subject ID	Iliac Crests		Bones		Skin		Outer Abdominal Wall	
	left	right	mean	std	mean	std	mean	std
1	1.4144	3.0660	2.4661	5.1516	1.2993	1.1746	1.3336	1.2167
2	3.0588	3.0588	2.2341	3.3868	1.1301	0.7444	2.5176	2.5225
3	6.0216	9.0144	2.2301	3.6903	1.0254	0.6091	1.1448	1.0666
4	1.2754	2.0565	2.0430	0.8984	1.2103	1.0083	1.3245	1.4163